SYNOPSIS OF RESEARCH PROJECT

1.	**Name of Student**	: GAVIT PRIYANKA LAXMAN
2.	**Registration No.**	: 1050225006
3.	**Faculty**	: Agricultural Engineering & Technology
4.	**Name of Degree Submitted for**	: Ph.D.
5.	**Major Subject**	: SOIL AND WATER CONSERVATION ENGINEERING
6.	**Minor Subject**	: IRRIGATION AND DRAINAGE ENGINEERING
7.	**Name of Major Guide**	: Dr. H. V. Parmar Professor, Department of Soil and Water Conservation Engineering, College of Agricultural Engineering and Technology, Junagadh Agricultural University, Junagadh
8.	**Title of the Research Project**	: **ESTIMATION OF CROP WATER STRESS USING INTERNET OF THING (IoT) BASED THERMAL REMOTE SENSING**

9. Introduction

Global water security is increasingly threatened by the agricultural sector's heavy reliance on freshwater, which currently accounts for approximately 70% of worldwide withdrawals. This demand is exacerbated by the compounding pressures of rapid population growth, climatic volatility, and inconsistent precipitation, particularly in arid and semi-arid zones where water shortages severely limit agricultural output. Consequently, integrating scientific irrigation strategies to optimize water use efficiency is a critical prerequisite for achieving sustainable food systems and mitigating the impact of environmental scarcity (Katimbo *et. al.*, 2022).

Water is a critical input for crop growth and plays a fundamental role in physiological and biochemical processes such as photosynthesis, transpiration, nutrient transport and temperature regulation. However, due to declining water resources and increasing competition among agricultural, industrial and domestic sectors, efficient utilization of available water has become imperative.

Crop water stress occurs when the water available in the soil is insufficient to meet the transpiration needs of the plant. This stress condition affects physiological processes such as photosynthesis, stomatal conductance and nutrient uptake, ultimately leading to reduced crop yield (DeJonge *et. al*., 2015). In response to water deficit, plants trigger stomatal closure as a survival mechanism to minimize transpiration; however, this concurrently restricts carbon dioxide intake and inhibits photosynthesis. Such prolonged physiological stress negatively impacts biomass production, root system architecture, and final crop quality (Gonzalez-Dugo *et al*., 2020). Consequently, identifying water stress at its onset is vital for precision irrigation management, which helps maintain plant health while preventing resource waste through runoff or deep percolation. Addressing the spatial and temporal fluctuations of water availability is therefore a fundamental requirement for optimizing water-use efficiency in modern agricultural systems.

Traditionally, crop water status has been assessed using soil moisture measurements, plant-based indicators (such as leaf water potential) and visual observations. Soil moisture sensors provide direct information about water availability in the root zone, while plant-based measurements reflect the physiological response of crops to water deficit. However, these methods are often destructive, labour-intensive, time-consuming and limited in spatial coverage (DeJonge *et. al*., 2015). Moreover, they may not provide continuous real-time data required for dynamic irrigation management. Visual assessment methods are subjective and may fail to detect early stress symptoms, leading to delayed irrigation decisions. As a result, there is a growing need for modern, non-invasive and scalable techniques for monitoring crop water stress in real time. Advanced sensing technologies and remote sensing approaches have gained significant attention in recent years due to their ability to provide rapid, accurate and spatially distributed information about crop conditions. These technologies enable farmers and researchers to make data-driven decisions for improving crop productivity and resource use efficiency.

Thermal remote sensing has emerged as an effective tool for detecting crop water stress based on canopy temperature measurements. Remote sensing is helpful for estimation of land surface temperature which can be correlated with vegetation index (Parmar and Gontia, 2019) and also to estimate crop evapotranspiration (Parmar and Gontia, 2016, 2021, 2022).When plants experience adequate water supply, transpiration helps cool the canopy surface. In contrast, water-stressed plants exhibit

reduced transpiration, leading to increased canopy temperature (Jackson *et. al*., 1981). In agricultural water management, the variance between canopy and ambient air temperature serves as a critical metric for evaluating plant water status and identifying physiological stress. As highlighted by (Katimbo *et. al*., 2022), infrared thermometry facilitates the continuous and non-invasive monitoring of these temperatures across multiple scales, utilizing platforms ranging from manual handheld sensors to ground-based stations and unmanned aerial vehicles (UAVs). The primary utility of thermal remote sensing is its capacity to synthesize environmental data with crop physiological feedback, providing a robust and integrated indicator of irrigation requirements and water-deficit stress.

Canopy temperature serves as a vital physiological indicator that can be evaluated independently or integrated into standardized metrics like the Crop Water Stress Index (CWSI). By normalizing the gradient between the plant temperature and the surrounding air, the CWSI effectively accounts for fluctuating environmental variables, providing a more stable assessment of crop water status across diverse conditions (Idso *et. al*., 1981). The CWSI is one of the most widely accepted indicators of plant water stress and is calculated using upper and lower temperature limits representing fully stressed and non-stressed conditions. It provides a quantitative measure of stress ranging from 0 (no stress) to 1 (maximum stress). The CWSI has been successfully applied for irrigation scheduling in various crops, including wheat, maize, cotton and sugarcane (DeJonge *et. al*., 2015; Katimbo *et. al*., 2022; Gontia and Tiwari, 2008). It has shown strong relationships with other plant and soil-based indicators such as soil moisture content, stomatal conductance and leaf water potential. However, the accuracy of CWSI depends on proper determination of baseline conditions and environmental factors such as solar radiation, wind speed and humidity.

Recent advancements in the Internet of Things (IoT) have further enhanced the potential of thermal sensing technologies in agriculture (Buyya *et. al*., 2013; Raza *et. al*., 2017). IoT-based systems integrate sensors, wireless communication, cloud computing and data analytics to provide real-time monitoring and decision support (Roopaei *et. al*., 2017). These systems enable continuous collection of field data and allow remote monitoring of crop conditions through mobile or web-based platforms (Gutierrez *et. al*., 2014). By combining IoT with thermal remote sensing, it becomes possible to continuously track canopy temperature, environmental parameters (such as

air temperature, humidity and solar radiation) and crop conditions (Anderson *et. al*., 2016). This integration facilitates automated data acquisition, real-time analysis and intelligent decision-making for irrigation scheduling. IoT-based systems can also reduce labor requirements and improve the efficiency of farm management practices (Roopaei *et. al*., 2017).

Furthermore, the integration of IoT and thermal sensing supports precision agriculture by enabling site-specific management of crops (Stafford, 2000). It allows farmers to apply water only where and when it is needed, thereby reducing water wastage and improving crop productivity (Sanchez *et. al*., 2018). The use of wireless sensor networks and cloud-based platforms also enhances data accessibility and scalability of the system (Raza *et. al*., 2017; Buyya *et. al*., 2013).

Wheat (*Triticum aestivum* L.) is one of the most important cereal crops globally and serves as a staple food for a large portion of the world's population. In India, Wheat is a major rabi crop contributing significantly to food security and agricultural economy (Sharma *et. al*., 2015). It occupies a significant share of cultivated land and plays a vital role in ensuring nutritional security. Wheat productivity is profoundly influenced by moisture availability, with (Gontia and Tiwari, 2008) noting that water deficits at pivotal phenological phases specifically tillering, anthesis, and grain filling result in significant yield penalties. Drought stress during flowering disrupts grain set and formation, whereas inadequate moisture during the grain-filling period diminishes individual grain weight and overall nutritional quality. Consequently, maintaining optimal soil moisture during these sensitive growth windows is essential for preserving both the quantitative yield and the qualitative standards of the harvest.

Efficient irrigation management is therefore essential to ensure optimal Wheat production. However, conventional irrigation practices often rely on fixed schedules rather than actual crop water requirements, leading to either over-irrigation or under-irrigation. Over-irrigation results in water wastage, nutrient leaching and increased production costs, whereas under-irrigation leads to yield reduction.

In this context, advanced technologies such as IoT-based thermal remote sensing provide a promising solution for real-time monitoring of crop water stress and precision irrigation management. These technologies enable continuous assessment of crop conditions and allow timely interventions to minimize stress and maximize productivity.

This research proposes the design of an IoT-integrated thermal remote sensing framework to quantify water stress in wheat crops. By combining ground-level IoT sensor networks with high-resolution thermal imaging, the system will facilitate the real-time monitoring of canopy temperature fluctuations alongside critical agro meteorological variables. This dual-layered approach aims to provide a continuous, data-driven assessment of crop water requirements, enhancing the precision of irrigation scheduling through the synchronization of localized environmental data and remote sensing diagnostics. Thermal remote sensing-based indices, such as canopy temperature-based stress indicators, will be derived and compared with IoT sensor-based measurements.

The proposed study will employ a correlation analysis integrating thermal indices, ground-truth measurements, and real-time IoT data to facilitate the precise detection of crop water stress. By synthesizing these diverse data streams, the methodology aims to establish a robust framework for dynamic irrigation scheduling. Ultimately, this approach is designed to optimize wheat cultivation by minimizing unnecessary water consumption and significantly improving overall water use efficiency through accurate, data-driven decision-making. Ultimately, this research will contribute to sustainable agriculture by promoting smart irrigation practices and optimal utilization of water resources.

10. Practical Utility of the Research Project

Sustainable water management and precision irrigation rely heavily on the prompt and precise identification of crop water deficits. Thermal remote sensing has emerged as a robust methodology for monitoring these conditions by measuring canopy temperature, a key indicator that directly correlates with plant transpiration rates and overall hydration status. However, conventional methods based on ground based measurement satellite data are limited by high cost, low temporal resolution, weather dependency, and restricted accessibility for small-scale farmers.

To overcome these limitations, the integration of Internet of Things (IoT) with thermal sensing offers a reliable solution. IoT-based systems enable continuous, real-time and automated monitoring of crop conditions directly at the field level. This research proposes a novel integration of IoT and thermal remote sensing, combining the strengths of both approaches to develop a cost-effective, high-resolution and efficient system for crop water stress estimation.

11. Objectives

1. To develop Internet of Tings (IoT) based thermal remote sensing system.
2. To measure crop temperature using IoT based thermal remote sensing.
3. To estimate the crop water stress using thermal remote sensing.

12. Review of Literature

This section provides an extensive evaluation of current literature concerning the assessment of crop water stress, the utilization of remote sensing technologies, and the integration of these methodologies within precision irrigation frameworks. The review is systematically organized into specific sub-sections to clearly highlight different aspects relevant to the present study.

Gontia and Tiwari (2008) developed empirical baseline equations to relate canopy air temperature difference (T_c-T_a) with vapour pressure deficit (VPD) under non-stress and fully stressed conditions in Triticum aestivum. Using infrared thermometry, they established linear relationships between Tc-Ta and VPD, forming lower (non-stressed) and upper (fully stressed) baselines for estimating the Crop Water Stress Index (CWSI). The experiment was conducted under a randomized block design with irrigation treatments based on maximum allowable depletion (MAD) of available soil water (10%, 40%, 60%, along with fully irrigated and fully stressed conditions). The study reported that T_c-T_a and VPD showed strong linear correlations, with slope (m) and intercept (c) values for the lower baseline as m = 1.7466, c = 1.2646 (pre-heading stage) and m = 1.1141, c = 2.0827 (post-heading stage). Using these relationships, CWSI was successfully quantified for different irrigation schedules. The findings suggest that the calculated Crop Water Stress Index (CWSI) serves as a precise metric for tracking plant water requirements. Consequently, this index provides a dependable framework for optimizing irrigation timing in wheat cultivation across diverse soil moisture regimes.

Krishna *et al.* (2019) utilized thermal and hyperspectral remote sensing to evaluate drought stress responses in various rice genotypes. By analyzing the relationship between the Crop Water Stress Index (CWSI) and Relative Water Content (RWC), the study established a significant inverse correlation (R^2=0.63), confirming that elevated canopy temperatures serve as a reliable indicator of reduced plant water status. The researchers further employed Partial Least Squares (PLS) regression to model CWSI using spectral reflectance across the 350–2500 nm range, identifying ten critical wavebands for stress detection while noting that 5 nm intervals optimized data

efficiency. Genotype screening categorized APO and Pusa Sugandha-5 as drought-tolerant, whereas varieties such as CR-143 and Pusa Basmati-1 were identified as highly sensitive. Ultimately, the study highlights the efficacy of integrating multi-sensor remote sensing for the high-throughput phenotyping and early identification of water stress in rice cultivation.

Ahmad *et al.* (2021) conducted a comprehensive study on the application of remote sensing techniques for evaluating crop water stress under varying environmental conditions. The researchers emphasized that spectral indices derived from optical and thermal remote sensing can effectively estimate plant water status with high spatial and temporal resolution. The study identifies land surface temperature (LST) and evapotranspiration (ET) as vital indicators of water stress, using thermal imaging to show that elevated canopy temperatures characterize moisture-deficient crops. By fusing sun-induced chlorophyll fluorescence (SIF) with multispectral and hyperspectral data, the researchers enhanced the accuracy of early-stage stress detection. Ultimately, the research concludes that integrating diverse platforms including satellite systems, hyperspectral sensors, and LiDAR improves the precision of irrigation management and suggests that future real-time data integration will further optimize precision agriculture applications.

Chandel *et al.* (2022) conducted a comprehensive study on non-invasive detection of crop water stress in winter wheat using advanced computer vision techniques combined with thermal and RGB imagery. The experiment was carried out over two growing seasons under controlled irrigation treatments, including flood and sprinkler systems with varying irrigation levels (100%, 75%, 50% and 25% of crop evapotranspiration, ETc). A large dataset of about 3200 images was collected at key growth stages (20 to 108 days after sowing) using a custom-built thermal-RGB imaging system. The study revealed that irrigation levels significantly influenced plant physiological parameters. Well-irrigated crops (100% ETc) exhibited lower canopy temperature (~22.5°C), higher relative water content (~90%) and higher soil moisture (~25.7%), whereas water-stressed crops (25% ETc) showed increased canopy temperature (~28°C) and reduced plant water status. For stress classification, deep learning models such as ResNet50 achieved the highest accuracy (up to 98.4% with thermal imagery), outperforming other models. Additionally, among machine learning approaches, DL-LSTM provided strong performance (96.7% accuracy) in distinguishing stressed and non-stressed crops. The findings emphasized that thermal

imagery is more effective than RGB data and demonstrated the potential of integrating computer vision and AI for precise and high-throughput crop water stress monitoring.

Katimbo *et al.* (2022) conducted their study in the Central Nebraska evaluated multiple approaches for estimating Index semi-arid region of West the Crop Water Stress (CWSI) using canopy temperature data obtained from stationary infrared thermometers (IRTs) and thermal imaging techniques. The researchers compared theoretical methods (CWSI-Th1 and CWSI-Th2), empirical baseline approaches (CWSI-EB1 and CWSI-EB2) and methods based on artificial and natural reference surfaces (CWSI-EA and CWSI-EN). The results indicated that the method used to establish upper and lower baselines significantly affects the accuracy and range of CWSI values. The empirical lower baseline developed during the 2020 maize growing season showed a strong linear relationship between canopy-air temperature difference and vapor pressure deficit ($Tc - Ta = 1.37 \times VPD + 1.82$), with a correlation coefficient ($R \approx 0.8$). All CWSI approaches demonstrated higher sensitivity to soil high 2 water depletion beyond 80%, particularly at deeper soil depths (1.8 m and 2.1 m). Among the methods, CWSI-Th2 exhibited the highest sensitivity, followed by CWSI- EB2 and CWSI-Th1, while CWSI-EN showed the least sensitivity. Additionally, strong positive correlations were observed between CWSI values and soil water depletion, with CWSI-Th1 showing the highest correlation ($r \approx 0.8$ at 2.1 m depth), followed by CWSI-EB2 and CWSI-EB1. The study concluded that CWSI values vary depending on the method used and daily fluctuations may not always accurately reflect soil moisture status. Therefore, method-specific threshold values are necessary for effective irrigation scheduling.

Awais *et al*. (2023) explored the efficacy of UAV-mounted thermal sensors for mapping the Crop Water Stress Index (CWSI), particularly within water-scarce agricultural systems. Their research demonstrated that high-resolution infrared imagery accurately captures canopy temperature fluctuations, which serve as a reliable proxy for soil moisture and plant hydration levels. The study validated the UAV-derived CWSI by showing a strong correlation with traditional ground-based metrics, proving its ability to quantify spatial and temporal stress variability. Key findings highlighted that UAV platforms offer superior flexibility, rapid data collection, and higher spatial resolution compared to conventional monitoring techniques. Ultimately, the authors concluded that integrating thermal sensing into

irrigation scheduling allows for optimized water application and improved crop productivity, providing a scalable solution for precision water management in semi-arid regions.

Dwivedi *et al.* (2024) conducted a study to analyze canopy air temperature difference and vapour the relationship between pressure deficit (VPD) in wheat under non-stress conditions for estimating was to the Crop Water Stress Index (CWSI). The study develop baseline equations for better irrigation scheduling and water management. The experiment was carried out using a randomized block design (RBD) with five treatments representing different soil moisture levels, including full irrigation, no irrigation, and 10%, 30%, and 50% soil moisture deficits. Canopy–air temperature difference was measured and regressed against VPD to establish lower (non-stress) and upper (stress) baselines. The results showed a clear linear relationship between canopy temperature difference and VPD. The baseline parameters varied for different seasons and growth stages, such as m = −2.371 and c = −1.659 (pre-heading) and m = −1.8952 and c = −2.32 (post-heading) during 2018–2019, and m = −1.7184 and c = −2.3009 (pre-flowering) and m = −1.8137 and c = −1.9176 (post-flowering) during 2019–2020. The study also found that a 30% soil moisture deficit gave the highest water use efficiency. Using these equations, CWSI values were calculated for different irrigation conditions.

Wang *et al.* (2024) optimized water stress diagnostics in winter wheat by fusing UAV-derived thermal and multispectral data through various phenological stages. Their research revealed a temporal shift in indicator sensitivity: thermal indices (TIs) correlated most strongly with normalized stomatal conductance (NGS) and effective water content (EWC) during early growth, whereas vegetation indices (RVI, MSR, and NDVI) proved superior in later stages. By evaluating several machine learning algorithms, the authors identified the Gradient Boosting Decision Tree (GBDT) as the most precise model, reaching R^2 values of 0.88 for NGS and 0.90 for EWC. Ultimately, the study found that integrating multi-source imagery significantly enhances prediction accuracy, particularly during post-heading growth stages compared to earlier developmental periods.

Yadav *et al.* (2024) focused on estimating the Crop Water Stress Index (CWSI) using machine learning approaches, including support vector regression (SVR), artificial neural networks (ANN), random forest regression (RFR) and multiple linear regression (MLR). The models were trained using key soil-plant- atmosphere

variables such as canopy temperature (Tc), air temperature (Ta), vapor pressure deficit (VPD), net radiation (Rn), wind speed (U) and soil moisture depletion (SD), under different input combinations. The findings revealed that SVR outperformed all other models, achieving the lowest prediction error, with mean absolute error (MAE) ranging from 0.90 to 1.47%, followed by ANN (2.03-3.08%), RFR (4.92-5.93%) and MLR (13.71-13.99%). The most effective input combinations varied across models, with C6 (Tc, Ta, VPD, Rn, U) for SVR, C8 (all variables) for ANN and MLR and C3 (Tc, Ta, VPD, U) for RFR. Among the variables, net radiation (Rn) was most influential for SVR and MLR, while wind speed (U) was significant for ANN. The study also highlighted that machine learning models can successfully capture the nonlinear interactions within the soil-plant-weather system and eliminate the need for empirical baseline temperature calculations required in traditional CWSI estimation. Overall, the research demonstrated that SVR is a reliable and efficient tool for CWSI prediction, with strong potential for application in irrigation scheduling and decision support systems to improve water use efficiency.

Mali *et al*. (2025) utilized UAV-based thermal and multispectral imaging to analyze the spatiotemporal dynamics of water stress in wheat. By calculating the Crop Water Stress Index (CWSI) through canopy temperature and atmospheric variables, the researchers compared various predictive frameworks, including linear regression and machine learning algorithms such as Random Forest (RF), Decision Tree (DT), and Support Vector Machine (SVM). The RF model emerged as the most robust, yielding R^2 values between 0.85 and 0.90. Their findings indicate that integrating thermal data with vegetation indices (VIs) across multiple growth stages enhances prediction accuracy more effectively than single-stage analysis. Ultimately, the study confirms that combining UAV remote sensing with machine learning provides a precise tool for mapping field-scale variability and optimizing autonomous irrigation scheduling.

13. Materials and Methods

This chapter deals with the research project planning, material used, methodology and technique used in conducting the research work.

13.1 Description of the study area

13.1.1 Location

The experiment will be conducted at the Instructional Farm, College of Agricultural Engineering and Technology, Junagadh Agricultural University, Junagadh.

13.2 Year and season of experiment

Year: 2026-27

Season: Rabi

13.3 Crop parameter

1. Crop: Wheat (Triticum aestivum L.)
2. Sowing time: November, 2026
3. Seed rate: 120 kg/ha
4. Basal application (kg/ha) W(120): P(60): K(60)
5. The crop stages of Wheat includes:
    i. Germination,
    ii. Tillering,
    iii. Stem elongation,
    iv. Heading,
    v. Flowering,
    vi. Grain filling and
    vii. Ripening stages.

13.4 Crop water stress using IoT system

IoT-based crop water stress include modules, cameras and sensors. The IoT system includes sensors that record real-time ground data, such as temperature, relative humidity, and soil moisture levels. This sensor provides useful information for crop water stress. Python will be used to program the IoT system. The major components of IoT systems are listed below.

13.4.1 Raspberry pi 5 model

- **Role:** The CPU for sensor data processing, image capture and cloud communication.
- **Specifications:**
    - Processor: Quad-core 1.2 GHz
    - Memory: 4 GB RAM
    - Connectivity: Wi-Fi (2.4GHz), Bluetooth 5.1
    - GPIO Pins: 40 for sensor/actuator interfacing
    - Power: 5V, ~2.5A via micro-USB

- Ports: 4x USB 2.0, HDMI, 3.5mm audio, CSI (camera), DSI
- (display), 40-pin GPI

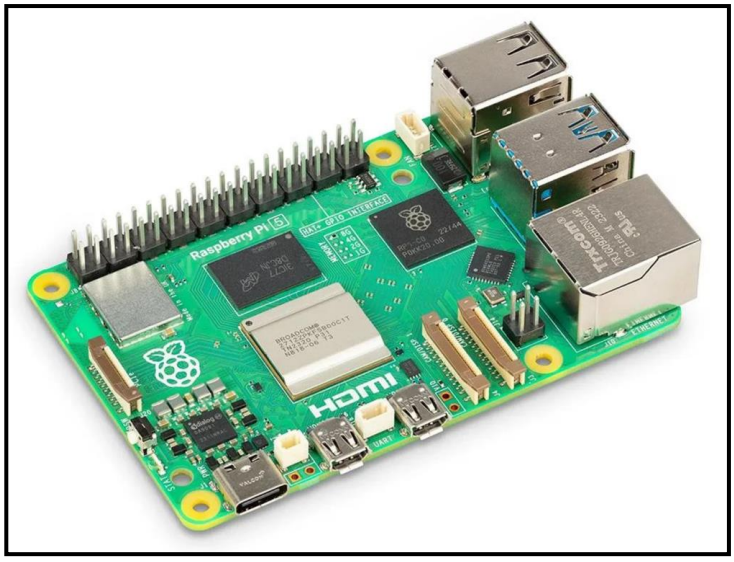

Figure 1. Raspberry Pi 5 model

13.4.2 Raspberry pi thermal camera module

- **Role:** Thermal images for crop water stress
- **Specifications:**
  - **Sensor:** 1×7semi MLX90640 IR Thermal camera
  - **Resolution:** (3280x2464)
  - **Current Consumption:** <23mA
  - **Field of View:** -110×75 degrees
  - **Operating Temprature**: -40 ~ 85◦C
  - **Power:** <250mA at 3.3V

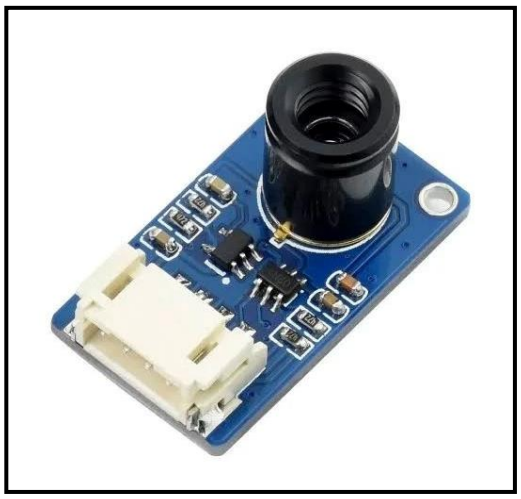

Figure 2. Raspberry Pi thermal camera module

13.4.3 Power source (Solar panel with battery)

- **Role:** Powers the system in field conditions.
- **Specifications:**
  - Solar Panel: 10W, 12V
  - Battery: 12V, 7Ah Li-ion
  - Output: 5V/3A via regulator for Raspberry Pi

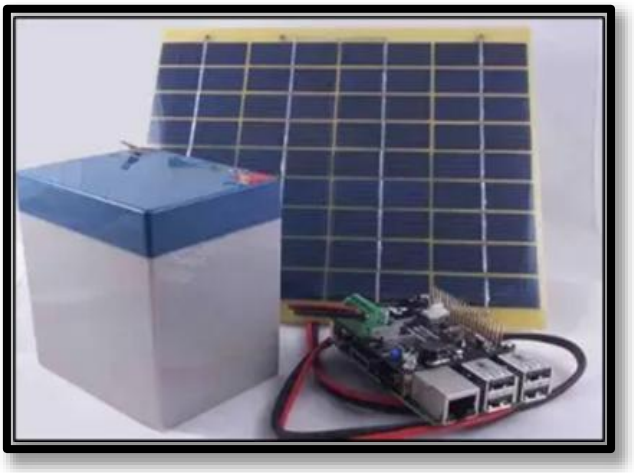

Figure 3. Solar panel with battery

13.4.4 Cloud platform

Role: This is used for Storing images and visualizes images.

13.4.5 Crop Temperature Measurement

The proposed research involves developing an IoT-integrated thermal remote sensing system to record crop thermal imagery over various time intervals. These data will be processed to generate detailed thermal maps, providing precise temperature measurements in degrees Celsius. To validate the remote sensing findings, crop canopy temperatures will be simultaneously recorded using an infrared thermometer across the same durations, ensuring accurate correlation and monitoring.

13.4.5.1 Crop water stress index = CWSI

The CWSI was calculated using the method of Idso *et. al.,* (1981) The proposed methodology normalizes calculated canopy temperatures by scaling them between the theoretical minimum of a non-stressed crop and the maximum observed under extreme water deficit. To establish the lower baseline, the relationship between the canopy-to-air temperature differential (T_c-T_a) and vapor pressure deficit (VPD) was derived exclusively from fully irrigated control plots. Conversely, the upper stress

threshold was determined using data from the total irrigation deficit treatment, following established analytical protocols.

Idso *et. al.,* (1981) CWSI is as follows:

$$CWSI = \frac{[(T_c - T_a) - (T_a - T_a)_{ll}]}{[(T_c - T_a)_{ul} - (T_c - T_a)_{ll}]} \quad \text{… Eq. 1}$$

Where,

T_c = canopy temperature (◦C),

T_a = air temperature (◦C),

The lower baseline (ll) is defined by measurements taken from fully irrigated, non-water-stressed treatments (0% deficit). Conversely, the upper limit (ul) represents a non-transpiring state, derived from data collected under conditions of total water deprivation (100% deficit).

13.4.5.2 Thermal condition index (TCI)

It works by comparing current temperature conditions with historical temperature extremes of a particular area to determine whether crops are experiencing stress. When plants face water deficiency, their canopy temperature increases due to reduced transpiration, and TCI helps in identifying this stress condition effectively. The index ranges from low to high values, where lower values indicate severe thermal stress or drought conditions, and higher values represent favorable conditions with adequate moisture availability. TCI is widely used in agricultural drought monitoring, crop health assessment and irrigation management because it provides reliable large-scale information even in areas where ground data is limited. (Kogan, 1995).

13.4.6 Infrared thermometer

An infrared thermometer is a hand held device used to measure crop temperature without touching an object. It works by detecting the heat (infrared radiation) coming from the surface and converting it into a temperature reading. It is very fast and easy to use, and it shows the result on a digital screen. In agriculture, it is used to measure crop canopy temperature, which helps to know if plants are under water stress.

13.4.7 Flowchart for estimation of crop water stress index

For this research project Raspberry Pi 5 Model will use as system's central processing unit. It will receive the input photographs from Raspberry Pi Thermal Camera Module. The Raspberry Pi will be powered by an external source (solar power). All data will be collected and processed and then transferred to the cloud for

further analysis and storage. The data from the cloud will be accessed and shown using GEE and geographic information system application will be used for mapping and spatial data processing.

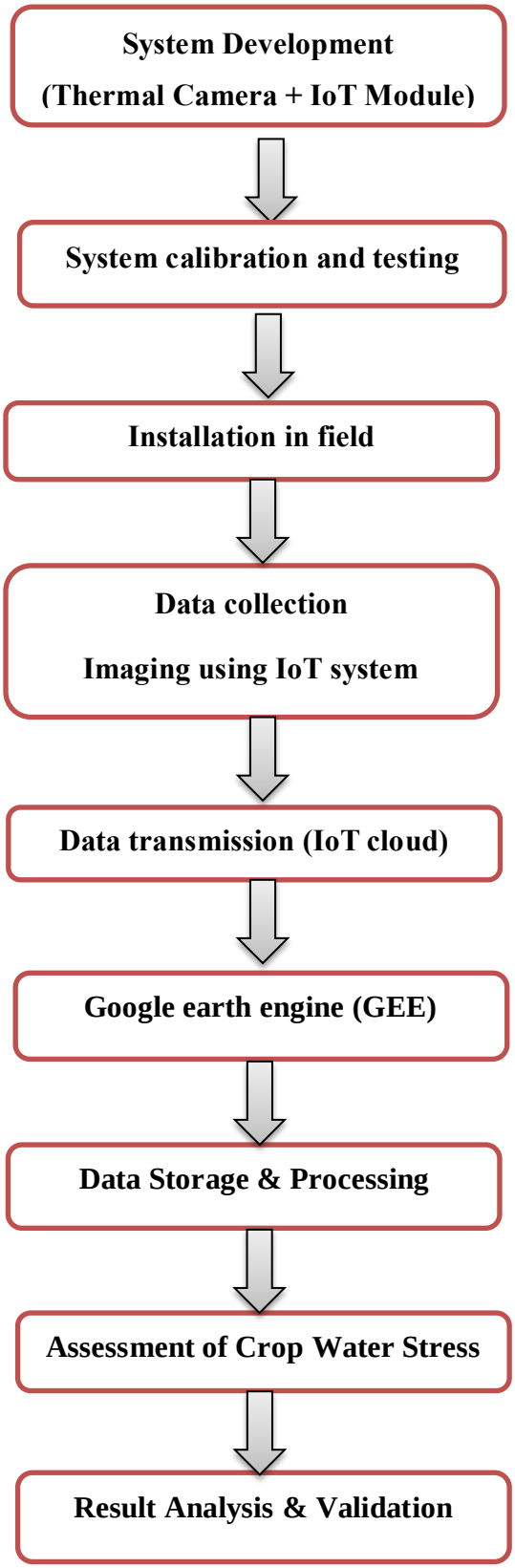

Figure 4. Flowchart for estimation of crop water stress

13.5 Observations to be recorded

a. Temporal and Spatial thermal images using developed IoT system

b. Air temperature and leaf temprature

c. Crop parameters, Crop stage, Crop height

14. Statistics Analysis

Correlation and Regression will be carried out as per standard method given by Miles and Shevlin, (2000) to develop the relationship. To check the accuracy of the developed relationships for the collected data will be used Coefficient of determination, root mean square, mean absolute error, etc.

1. Coefficient of determination (R^2)

$$\text{RSS} = 1 - \frac{RSS}{TSS} \quad \text{… Eq. 2}$$

Where,

Residuals Sum of Squares = RSS = $\sum_{i=1}^{n}(y_i - y_p)^2$

Total Sum of Squares = TSS = $\sum_{i=1}^{n}(y_i - \bar{y})^2$

Where,

n = the total number of observation data

y_i = observed data

y_p = predicted data

$\bar{y}$ = average value of y_i

2. Root Mean Square Error = RMSE

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_p)^2} \quad \text{… Eq. 3}$$

15. References

Ahmad, U., Alvino, A., and Marino, S. (2021). A review of crop water stress assessment using remote sensing. *Remote Sensing*, **13(20)**: 4155-4173.

Anderson, Martha C., Cornelio A. Zolin, Paulo C. Sentelhas, Christopher R. Hain, Kathryn Semmens, M. Tugrul Yilmaz, Feng Gao, Jason A. Otkin, and Robert Tetrault. "The Evaporative Stress Index as an indicator of agricultural drought in Brazil: An assessment based on crop yield impacts."*Remote Sensing of Environment*, **174 (2016):** 82-99.

Awais, M., Li, W., Cheema, M. J. M., Zaman, Q. U., Shaheen, A., Aslam, B. and Liu, C. (2023). UAV-based remote sensing in plant stress imagine using high-

resolution thermal sensor for digital agriculture practices: A meta-review. *International Journal of Environmental Science and Technology*, **20(1):** 1135-1152.

Chandel, N. S., Rajwade, Y. A., Dubey, K., Chandel, A. K., Subeesh, A. and Tiwari, M. K. (2022). Water stress identification of winter wheat crop with state-of-the-art AI techniques and high-resolution thermal-RGB imagery. *Plants*, **11(23):** 3344-3375.

DeJonge, K. C., Taghvaeian, S., Trout, T. J. and Comas, L. H. (2015). Comparison of canopy temperature-based water stress indices for maize. *Agricultural Water Management*, **156**: 51–62.

Dwivedi, A. K., Ojha, C. S. P. and Singh, V. P. (2024). Crop water stress index for scheduling irrigation of wheat crop. *Journal of Irrigation and Drainage Engineering,* **150(3):** 04024006-04024015.

Gontia, N.K. and Tiwari, K.N. (2008). Development of crop water stress index of wheat crop for scheduling irrigation using infrared thermometry. *Agricultural Water Management,* **95(10)**: 1144-1152.

Gonzalez-Dugo, V., Zarco-Tejada, P.J. and Nicolas, E. (2020). Thermal imaging for crop water stress detection. *Remote Sensing of Environment*. **13(26):** 3343-3360.

Gubbi, J., Buyya, R., Marusic, S. and Palaniswami, M. (2013).Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems*, **29(7):** 1645–1660.

Gutierrez, J., Villa-Medina, J. F., Nieto-Garibay, A. and Porta-Gandara, M. A. (2014). Automated irrigation system using a wireless sensor network and GPRS module. *IEEE Transactions on Instrumentation and Measurement*, **63(1):** 166–176.

Idso, S. B., Jackson, R. D., Pinter, P. J., Reginato, R. J. and Hatfield, J. L. (1981). Normalizing the stress-degree-day parameter for environmental variability. *Agricultural Meteorology*, **24**: 45–55.

Jackson, R. D., Idso, S. B., Reginato, R. J. and Pinter, P. J. (1981). Canopy temperature as a crop water stress indicator. *Water Resources Research*, **17(4)**: 1133–1138.

Katimbo, A., Rudnick, D. R., DeJonge, K. C., Lo, T. H., Qiao, X., Franz, T. E., Nakabuye, H. N. and Duan, J. (2022). Crop water stress index computation

approaches and their sensitivity to soil water dynamics. *Agricultural Water Management*, **266**: 107575-107590.

Kogan, F. N. (1995). Application of vegetation index and brightness temperature for drought detection. *Advances in space research*, **15(11):** 91-100.

Krishna, G., Sahoo, R. N., Singh, P., Patra, H., Bajpai, V., Das, B. and Chinnusamy, V. (2021). Application of thermal imaging and hyperspectral remote sensing for crop water deficit stress monitoring. *Geocarto International*, **36(5)**: 481-498.

Mali, S. S., Scobie, M., Baillie, J., Plant, C., Shammi, S. and Das, A. (2025). Integrating UAV-based multispectral and thermal infrared imageries with machine learning for predicting water stress in winter wheat. *Precision agriculture*, **26(3):** 44-50.

Parmar, H.V. and Gontia, N.K. (2016). Remote sensing based vegetation indices and crop coefficient relationship for estimation of crop evapotranspiration in Ozat-II canal command. *Journal of Agrometeorology*. **18(1):**137-139.

Parmar, H. V. and Gontia, N.K. (2019). Derivation of land surface temperature using satellite imagery and its relationship with vegetation index. *Journal of Agrometeorology*. **21 (1):** 104-106.

Parmar, H. V. and Gontia, N. K. (2021). Estimation of Evapotranspiration using Remote Sensing and Surface Energy Balance Algorithm for Land (SEBAL) in Canal Command. *Journal of Agricultural Engineering*. **58(3):** 274-285.

Parmar, H.V. and Gontia, N.K. (2022). Evapotranspiration Estimation Using Surface Energy Balance-Based Evaporative Fraction for Water Management in Canal Irrigation Command. *Journal of the Indian Society of Remote Sensing*. **50 (2)**: 373–384.

Raza, U., Kulkarni, P. and Sooriyabandara, M. (2017).Low power wide area networks: An overview for IoT-based applications. *IEEE Communications Surveys & Tutorials,* **19(2)**: 855–873.

Roopaei, M., Rad, P. and Choo, K. K. R. (2017). Cloud of things in smart agriculture: Intelligent irrigation monitoring by thermal imaging. *IEEE Cloud Computing*, **4(1)**: 10–15.

Sharma, I., Tyagi, B. S., Singh, G., Venkatesh, K. and Gupta, O. P. (2015). Enhancing wheat production-A global perspective. *The Indian Journal of Agricultural Sciences*, **85(1)**: 3-13.

Stafford, J. V. (2000). Implementing precision agriculture in the 21st century. *Journal of Agricultural Engineering Research,* **76(3)**: 267–275.

Wang, J., Lou, Y., Wang, W., Liu, S., Zhang, H., Hui, X. and Maes, W. H. (2024). A robust model for diagnosing water stress of winter wheat by combining UAV multispectral and thermal remote sensing. *Agricultural Water Management*, **291**: 108616-108635.

Yadav, A., Narakala, L. M., Upreti, H. and Das Singhal, G. (2024). Evaluation of crop water stress index of wheat by using machine learning models. *Environmental Monitoring and Assessment*, **196(10)**: 970-972.

Signature of student	**Signature of major guide**
(Gavit Priyanka Laxman)	**(Dr. H. V. Parmar)**